Net stable funding ratio and profit efficiency of commercial banks in the US

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Abstract

The net stable funding ratio (NSFR) is introduced under Basel III to promote financial stability. Under this new regulation, individual financial institutions are required to maintain a sustainable funding structure; hence this new universal requirement is expected to affect bank operation. In this paper, we provide one of the first empirical examinations of the non-linear relationship between NSFR and profit (in)efficiency for commercial banks using two data sets from Bankscope (for years from 2000 to 2015) and Federal Financial Institutions Examination Council call reports (2000-2013 period). Our results suggest that modest intensification in liquidity helps to reduce bank profit inefficiency (i.e. increase efficiency) but too much liquidity enlargement could increase the inefficiency. This result is consistent with a trade-off hypothesis on the non-linear relationship between liquidity and bank performance.

Keywords: NSFR, liquidity, profit inefficiency.

1. Introduction

Liquidity shortage is identified as one of the primary factors that have caused systemic instability in the financial systems before and during the global financial crisis (GFC) in 2007/08 (Acharya and Mora, 2015; Khan et al., 2016). To avoid liquidity shortfall, the Basel Committee on Banking Supervision (2010) proposed two liquidity principles under Basel III regulatory framework, namely Net Stable Funding Ratio (NSFR) and Liquidity Coverage Ratio (LCR). The NSFR aims at addressing long-term liquidity mismatch over a one-year horizon and the LCR targets at maintaining sufficient liquid assets to avoid the mismatch over a short-term (thirty days) horizon. Literature has shown that many banks need to change their management strategies (DeYoung and Jang, 2016; King, 2013; Schmaltz et al., 2014) and thus may have an adverse effect on their performance.

In general, there are two possible sets of actions that banks may take in response to the new regulations: better capitalization and balance sheet restructuring (Härle et al., 2010). First, to be safer in terms of liquidity, banks can increase their equity capital ratio because equity can play as a cushion for both capital and liquidity shortage. Moreover, banks with better capitalization can borrow long-term debts more easily and at lower costs (Modigliani and Miller, 1958). Second, banks might restructure their balance sheets, particularly assets and funding items because these items are used to compute the NSFR and LCR. For instance, to achieve higher NSFR and LCR, banks can hold more long-term funding (i.e. equity and deposits), which might incur more expenses than holding short-term funding. Banks might allocate more funding into liquid assets such as cash and securities on the asset side. These combined actions, however, limit maturity transformation (Dietrich et al., 2014), business model (Härle et al., 2010), and therefore influence bank performance.

Specifically, King (2013) highlights the well-known trade-offs between new liquidity requirements and profitability: the liquidity regulations should increase the resilience of banks during stressful periods but at the cost of a reduction in banks' profitability during normal times. In fact, concerns raised by banks that the liquidity requirements dramatically and adversely impact banks operation and profitability have led to the delayed implementation of the new liquidity requirements. However, only a few empirical studies examine the impacts of new liquidity requirements on bank performance since the announcement of BASEL III.

In the broader empirical literature on the effect of regulation on bank performance, studies either focus on accounting measures or use frontier analysis methods (Jakovljević et al., 2015). Dietrich et al. (2014) appear to be the first empirical examination on the impact of NSFR on bank profitability using the accounting measures. In the study, historical data of 921 Western European banks between 1996 and 2010 was used and empirical results showed that NSFR did not have a significant impact on banks' returns on assets and equity or net interest margin. Recently, Cai et al. (2019) show that with an increase in the NSFR in the U.S. banks would expect to experience a fall in their market power. However, to our best knowledge, there are neither empirical studies which investigate the relationship between NSFR and profit efficiency of banks in the United State of America (USA) nor empirical studies that use the frontier analysis method.

One advantage of using the frontier analysis method in analysing bank performance is its ability to benchmark the efficiency performance of each bank at each point of time with respect to the production frontier that underpins the production technology in the entire banking industry (Berger and Humphrey, 1997; Thanassoulis et al., 1996). Hence, using the frontier approach, our paper will be the first empirical study that investigates the non-linear relationship between bank profit efficiency and liquidity risk in terms of NSFR. We argue that this empirical relationship is important as NSFR captures liquidity risk, which reflects a different risk dimension from other types of risks such as credit risk (Berger and De Young, 1997), default likelihood (Fiordelisi et al., 2011), value-at-risk (Chang and Chiu, 2006), and systemic risk (Beccalli et al., 2015).

The non-linear relationship between bank efficiency and liquidity risk originates from the argument on a possible optimal level of capital or liquidity that bank managers set to achieve a certain level of profits (Delis, Hasan, and Tsionas, 2014). These authors assume that more efficient banks are more closely followed by both big creditors and depositors. Therefore, these banks hold less liquidity because they are easier to raise enough funds from interbank markets (wholesale liabilities) and loan sale markets. Whereas, less efficient banks may need to hold more liquidity because they are more difficult to raise enough funds to meet unexpected demands. The optimal level of liquidity shapes our idea that liquidity risk should be considered as a non-linear variable in explain efficiency level. The idea of the optimal level of liquidity is supported by previous studies of Buser, Chen, and Kane (1981) and Flannery (1994) which discuss the optimal capital structure of commercial banks.

Moreover, we expect the non-linear relationship between bank efficiency and liquidity risk because a bank implementing the NSFR may find a more liquidity-efficient business model when its maturity transformation is limited. Increasing liquidity might increase a bank's funding cost but does not necessarily lead to a reduction in accounting profit ratios such as return on assets, return on equity and interest margin (Dietrich, Hess, and Wanzenried, 2014), implicitly indicating a possibly equivalent or even greater increase in interest and non-interest income. Therefore, the marginal impact of liquidity risk on efficiency may change according to a bank's liquidity risk. In this sense, focusing on the linear relationship may have a biased result on the trade-off.

We use the frontier approach to examine a relationship between profit inefficiency and NSFR for commercial banks in the U.S. using two data sets from Bankscope (3,765 unique banks with 45,198 yearly observations) and Federal Financial Institutions Examination Council call reports (8,357 unique banks with 92,961 yearly observations). Empirical results from the stochastic frontier analysis favour an inverse U-shaped relationship between liquidity and bank inefficiency: greater liquidity is associated with lower inefficiency but too much liquidity might be associated with an increase in bank inefficiency.

The paper is structured as follow. Section 2 provides brief related literature. Sections 3 and 4 describe the methodology and data used. Section 4 presents the key findings. Section 6 provides a conclusion.

2. Related literature

A core function of commercial banks is to finance illiquid loans from customer deposits. Banking theories argue differing roles of the banks on the process of liquidity creation. Contemporary financial intermediation theories assume that banks are passive on the asset side because they simply allocate their granted loans (for a given fixed tenor) (Diamond and Dybvig, 1983; Ramakrishnan and Thakor, 1984). Normally, these loans are more illiquid than their customer deposits. A recent theory of banking namely “warehouse banking” of Donaldson, Piacentino, and Thakor (2018) argues that banks are more active on both sides of the balance sheet because they own warehouse technologies to manage client deposits as well as to enforce borrowers to repay their loans. By increasing more loans into the economy from the same amount of client deposits, banks are more efficient in the sense of earning more interest income and paying less cost of capital at the same time with a greater chance of liquidity shortage. This suggests a potential trade-off relationship between liquidity risk and efficiency.

Our study is also closely related primarily to the literature on the empirical relationship between credit risk and bank efficiency; hence we limit our literature review on this area of research with the focus on those studies on U.S.A. banks. A comprehensive study of Berger and De Young (1997) highlights four underlying mechanisms explaining the different mechanism that captures the relationship between credit risk and bank efficiency. First, decreases in efficiency tend to follow increases in risk, which supports the bad luck hypothesis. This hypothesis refers to the situation where an increase in credit risk results from an outside shock, beyond the bank's control. Efficiency falls because banks spend an increasing level of resources to deal with credit risk. Second, increases in risk follow falls in cost efficiency, which suggests the bad management hypothesis. The bad management hypothesis implies that bad management leads to excessive operating costs as well as poor risk monitoring practices, which results in lower efficiency and higher risk. Moreover, increases in risk are associated with higher costs of monitoring and selling off risk and thus this leads to a further decrease in cost efficiency. Third, increases in efficiency may lead to increases in risk and this favours the skimping hypothesis[1]. The skimping hypothesis implies a trade-off between short-run efficiency (via cost reduction or profit maximization) and long-run deterioration in asset quality. Finally, increases in leverage ratios for thinly capitalized banks tend to precede increases in non-performing loans (NPLs). This strengthens the moral hazard hypothesis that, in certain circumstances, bank managers alter their behaviour toward excessive risk-taking. Consequently, such moral hazard activity results in higher credit risk in the future. Among the four hypotheses, the trade-off between risk and efficiency is closer to the skimping view.

[1] In the short-term, one can argue that bank efficiency is positively correlated with credit risk as a bank chooses not to spend sufficient resources on analysing loan applications. If this lending practice remains, this could lead to higher levels of non-performing loans and the associated expenses to solve the problem loans in the long run.

The empirical literature has employed different measures of risks which are based on-balance-sheet and market data for examining the relationship between bank efficiency and risk. In terms of the balance-sheet risk, the most common type is credit risk proxied by NPLs. Berger and De Young (1997) use the SFA approach to measure cost efficiency in the first stage. Then they use non-performing loans (NPL) in the second stage to test for the relation. The advantage of using NPL lies at its less managerial discretion than loan loss provision and charge-offs, all of which stand for credit risk. Employing Granger causality techniques and a U.S commercial bank data sample for the period 1985–1994, they provide evidence for a negative interaction between risk and efficiency.

Berger and Mester (1997) assess the sources of efficiency of 6,000 US banks covering the period 1990-1995 using differing efficiency concepts, measurement methods, and bank, market, and regulatory characteristics. They argue that the quality of outputs has significant impacts on estimates of the efficiency level. In particular, differences in loan features, ranging from size, payment schedule, risk, collateral, covenants, etc., lead to differences in the cost of lending, monitoring and risk control. Most notably, Berger and Mester (1997) recognize that off-balance sheet items bear the same credit risk as loans. Their empirical results show that bad management practices could lead to high costs and low profits and high level of NPLs.

Outside the USA, recent literature argues that market-based measures (such as distance-to-default, expected default frequency, and systemic risk) could capture better the risk level of banks due to their forward-looking information and real-time basis (Beccalli et al., 2015; Chang and Chiu, 2006; Fiordelisi et al., 2011). Employing the two-stage DEA model, Chang and Chiu (2006) assess bank efficiency in Taiwan in which value-at-risk (VaR) and credit risk measured by NPL are viewed as undesired output in a cost efficiency model. Their finding hints that the risk factors matter and bank performance is lower when NPL and VaR increase. More recently Beccalli et al. (2015) examined how risk impacts scale economies (i.e. average cost reduction by increasing output level) for 103 listed banks in Europe over the period 2000-2011. Using different types of risks (i.e. liquidity ratio, loans loss provision ratio, Tier 1 capital ratio, off-balance-sheet risks, and systemic risk), the authors find that scale economies exist across quantiles of bank size and an increase in the first lag of systemic risk causes a fall in economies of scale.

Majority of the literature has focused on the relationship between risk and efficiency in the banking sector mainly employing credit risk, value at risk, and market risk. Little is known about how liquidity (risk), which played a key role in the safety of one and multiple banks during the GFC 2007-8, influences efficiency. Due to its importance, the Basel Committee on Banking Supervision (Basel Committee on Banking Supervision, 2010) introduced the Net Stable Funding Ratio (NSFR) to strengthen bank liquidity risk management practices. This paper fills the gap by investigating the relationship between this new liquidity standard and bank profit inefficiency. One of our focus is to empirically examine the possible trade-off between liquidity level and profit efficiency. In fact, our model allows for a non-linear relationship and examines the optimal level of liquidity in terms of its impact on bank efficiency.

3. Methodology

3.1. Profit efficiency estimation

Following recent empirical literature (Gaganis and Pasiouras, 2013; Luo, Tanna, and De Vita, 2016), we employ the Stochastic Frontier Analysis (SFA) approach in measuring efficiency and investigating the impact of liquidity on profit efficiency. The efficiency is constructed based on the concept of operational optimization in which bank profit can be considered as the output of the banks' operation. To allow for possible impacts of liquidity on the operation of banks, which results in the efficiency performance as well as the variation of efficiency across banks, we measure technical efficiency using a stochastic frontier model of Battese and Coelli (1995). This empirical model also allows us to control bank-specific characteristics in a single step of estimating efficiency and examining the determinants of variation of efficiency among banks. The model is specified as:

$$lnPBT_{i,t} = \pi(p_{i,t}, w_{i,t}; \beta) + (v_{i,t} - u_{i,t}), \tag{1}$$

where t denotes time dimension; $lnPBT_i$ is the logarithm of the profit before tax of bank i; $p_{i,t}$ is a vector of output prices; $w_{i,t}$ is a vector of input prices; β denotes a vector of unknown parameters to be estimated. $v_{i,t}$ is a random variable, which is assumed to be *i.i.d.* distributed as a $N(0, \sigma_v^2)$. $u_{i,t}$ is a non-negative random variable, which is assumed to account for the operational inefficiency. $u_{i,t}$ is estimated by truncation at zero of the $N(m_{i,t}, \sigma_u^2)$ distribution and $m_{i,t}$ is defined as:

$$m_{i,t} = z_{i,t-1}\delta, \tag{2}$$

where $z_{i,t-1}$ is a $(1 \times M)$ vector of explanatory variables (i.e. bank liquidity and characteristics) that influence the periodic inefficiency of each bank and explain variations in the inefficiency level among banks; δ is a $(M \times 1)$ vector of estimated coefficients. We follow Battese and Coelli (1995) in estimating β and δ in one step using maximum likelihood estimator.

We select bank inputs and output following the intermediation approach that views banks as agents that collect funds as inputs and allocate them into earning assets. As normally done in the empirical literature, banks are assumed to undertake lending and non-lending activities which are specified as two outputs. The prices for these outputs are defined as (i) the ratio of net interest income to net loans (P_1) and (ii) the ratio of non-interest income to other earning assets (P_2). We include three inputs: borrowing fund, labour and physical capital. The prices for the inputs are defined as the cost of borrowed fund (W_1), cost of labour (W_2), cost of physical capital (W_3). W_1 is calculated as the ratio of interest expenses to total deposits. W_2 is computed as the ratio of personnel expenses to total assets. W_3 is computed as the ratio of overhead expenses net of personnel expenses to fixed assets.

Following Gaganis and Pasiouras (2013), we include equity (EQ) as a proxy for bank risk profile in equation 1. We include EQ because ignoring EQ can lead to a scale bias originating from its twin roles: a cushion for risk and a funding source of bank outputs such as loans and investment (Berger and Mester, 1997). Furthermore, we include a dummy size variable (*Dummysize*) to capture the effect of bank size.

As normally done in the empirical literature, we normalize the dependent variable and all output and input prices by the cost of physical capital (W_3) and employ the Translog functional form. The estimated model is as follows:

$$
\begin{aligned}
\ln(PBT/W_3) = {} & \beta_0 + \beta_1 \ln\left(\frac{P_1}{W_3}\right) + \beta_2 \ln\left(\frac{P_2}{W_3}\right) + \beta_3 \ln\left(\frac{W_1}{W_3}\right) + \beta_4 \ln\left(\frac{W_2}{W_3}\right) \\
& + \beta_5 \frac{1}{2}\left(\ln\left(\frac{P_1}{W_3}\right)\right)^2 + \beta_6 \ln\left(\frac{P_1}{W_3}\right)\ln\left(\frac{P_2}{W_3}\right) + \beta_7 \frac{1}{2}\left(\ln\left(\frac{P_2}{W_3}\right)\right)^2 + \beta_8 \frac{1}{2}\left(\ln\left(\frac{W_1}{W_3}\right)\right)^2 \\
& + \beta_9 \ln\left(\frac{P_1}{W_3}\right)\ln\left(\frac{W_1}{W_3}\right) + \beta_{10} \ln\left(\frac{P_2}{W_3}\right)\ln\left(\frac{W_1}{W_3}\right) + \beta_{11} \frac{1}{2}\left(\ln\left(\frac{W_2}{W_3}\right)\right)^2 + \beta_{12} \ln\left(\frac{P_1}{W_3}\right)\ln\left(\frac{W_2}{W_3}\right) \\
& + \beta_{13} \ln\left(\frac{P_2}{W_3}\right)\ln\left(\frac{W_2}{W_3}\right) + \beta_{14} \ln\left(\frac{W_1}{W_3}\right)\ln\left(\frac{W_2}{W_3}\right) + \beta_{15} \ln(EQ) + \beta_{16} \frac{1}{2}(\ln(EQ))^2 \\
& + \beta_{17} \ln(EQ)\ln\left(\frac{P_1}{W_3}\right) + \beta_{18} \ln(EQ)\ln\left(\frac{P_2}{W_3}\right) + \beta_{19} \ln(EQ)\ln\left(\frac{W_1}{W_3}\right) \\
& + \beta_{20} \ln(EQ)\ln\left(\frac{W_2}{W_3}\right) + \beta_{21} T + \beta_{22} T \ln\left(\frac{P_1}{W_3}\right) + \beta_{23} T \ln\left(\frac{P_2}{W_3}\right) + \beta_{24} T \ln\left(\frac{W_1}{W_3}\right)
\end{aligned} \tag{3}
$$

$$+\beta_{25}T\ln\left(\frac{W_2}{W_3}\right)+\beta_{26}T\ln(EQ)+\beta_{27}Dummysize+v_{i,t}-u_{i,t}$$

To examine the direct impact of liquidity on (in)efficiency, we specify $m_{i,t}$ in equation 2 as:

$$m_{i,t}=f(Liquidity_{i,t-1},\ Bank\ characteristics_{i,t-1}), \tag{4}$$

where $Liquidity_{i,t-1}$ is the lagged value of bank liquidity. We employ the Basel III Accord's Net Stable Funding Ratio (NSFR) and core deposits-to-loans (DTL) ratio. Guided by empirical literature in banking sector, this paper uses four bank characteristic variables: the lagged value of asset diversification ($ADIV$), the lagged value of funding diversification ($FDIV$), the lagged value of logarithm value of total assets ($Size$) and the lagged value of non-performing loan ratio (NPL). We follow the approach of Curi et al. (2015) and Elsas et al. (2010) to compute $ADIV$ and $FDIV$. Specifically, in the computation of $ADIV$, the loans and advances to banks ($IBLOAN$), customer loans ($CLOAN$), and financial securities ($FSEC$) and other investments in property (IP) are used according to the following equation:

$$ADIV=1-\left(\left(\frac{IBLOAN}{EA}\right)^2+\left(\frac{CLOAN}{EA}\right)^2+\left(\frac{FSEC}{EA}\right)^2+\left(\frac{IP}{EA}\right)^2\right), \tag{5}$$

where earning assets (EA) is the sum of the four numerators.

In the calculation of funding diversification ($FDIV$), equity ($EQUI$), customer deposits ($CDEP$), deposits from banks ($IBDEP$), and other interest-bearing liabilities ($ODEBT$) are used as below:

$$FDIV=1-\left(\left(\frac{EQUI}{FUND}\right)^2+\left(\frac{CDEP}{FUND}\right)^2+\left(\frac{IBDEP}{FUND}\right)^2+\left(\frac{ODEBT}{FUND}\right)^2\right), \tag{6}$$

where $FUND$ is the sum of the four numerators.

3.2. Liquidity measurement

The paper employs two liquidity indicators as dependent variables. We use the *net stable funding ratio* (NSFR) and the core deposits-to-loans (DTL) ratio to proxy for bank liquidity. A high value of NSFR and DTL corresponds to a high level of liquidity. The NSFR is measured as:

$$NSFR = \frac{Available\ Stable\ Funding\ (ASF)}{Required\ Stable\ Funding\ (RSF)} = \frac{\sum_i w_i L_i}{\sum_j w_j A_j}, \qquad (7)$$

where the weights w_i and w_j are bounded between zero and one. The value of these weights reflects the stability of items in the bank balance sheet. The available stable funding (ASF) is the summation of bank liabilities and their corresponding weights. On the liability side, more stable funding sources are assigned greater weights. The *required stable funding* (RSF) is defined as the summation of bank assets and their corresponding weights. On the asset side, more liquid assets are assigned lower weights. A bank has low liquidity risk when its NSFR is high.

The BASEL III Accord calls the weights are ASF and RSF factors. These factors are specific weights applied to funding sources and assets. The weights corresponding to funding sources are called ASF factors, which represent the stability of the funding sources: more stable funds are assigned higher ASF factor. The weights corresponding to assets are called RSF factors. Unlike the ASF factor, a higher RSF factor represents less liquidity of an asset.

Table 1: Weights used to compute NSFR

TOTAL ASSETs	**Weight (%)**	**TOTAL LIABILITIES and EQUITIES**	**Weight (%)**
I. Earning assets		I. Deposits & short-term funding	
Loans	100	Customer deposits	
Other earning assets	35	+ Current deposits	85
		+ Saving deposits	70
		+ Term deposits	70
		Bank Deposits	0
II. Fixed assets	100	II. Other interest-bearing funding	
		Derivatives	0

		Trading liabilities	0
		Long term liabilities	100
		+ Total long-term liabilities	100
		+ Preferred shares	100
III. Non-earning assets		III. Noninterest-bearing funding	100
Cash and due from banks	0	IV. Reserves (for loan loss)	100
Goodwill and other intangibles	100	V. Other reserves	100
Other assets	100	VI. Owners' equity	100

Source: Vazquez and Federico (2015).

Due to unavailability of the information of bank assets and liabilities to compute the NSFR, we follow Vazquez and Federico (2015) in building up a "*stylized bank balance sheet*" and weights to approximate the NSFR ratio as shown in Table 1. Bankscope data set does not allow to split the loan portfolios into different types by residual maturity, which entail weight ranging from 50% to 100%. With a conservative view, we assign the maximum weight of 100% to the total loan portfolio and an average of 35% for other earning assets as BASEL III requests a range from 20% to 50% for other earning assets. For fixed assets and non-earning assets, we allocate the weight of 100%. On the liability side, we apply the BASEL III's ASF factors for each liability category.

For the data set from the Consolidated Reports of Condition and Income (Federal Financial Institutions Examination Council call reports), we follow the computation of NSFR as shown in the Appendix A (for period 2000-2011) and Appendix B (for period 2012-2013) in DeYoung and Jang (2016). Appendix A summarizes the components of ASF and RSF, the weights associated with each of these components, and the appropriate item numbers in the 1991 Statements of Condition and Income (call reports). As data structure of the call reports from 2014-now has changed significantly from that from before 2013 so we only compute the NSFR for the period 2000-2013 following DeYoung and Jang (2016) to make sure that the computational results are comparable.

In addition to the NSFR as our key liquidity indicator, we employ the core deposits-to-loans (DTL) ratio as another liquidity variable. The ratio presents a relative proportion between core deposits and gross loans. Thus, banks with a higher DTL ratio is more liquid than those with a lower ratio. We use the DTL rather than the LCR because the computation the LCR requiring certain unreported information such as high-quality liquid assets and projected net cash outflow for the next 30 days (Basel Committee on Banking Supervision, 2010) is not feasible (Dietrich et al., 2014). The use of DTL is also supported by the research of Acharya and Mora (2015) because DTL displays a liquidity shortfall of individual banks.

4. Data description

We obtain accounting information of commercial banks (CBs) in the U.S. from 2000 to 2015 from Bankscope and from 2000 to 2013 from Federal Financial Institutions Examination Council call reports (CALL reports). Variables used are defined in Table 2. We excluded all observations with missing and zero values. To mitigate the effect of outliers, we follow Acharya and Mora (2015b) in winsorizing all variables at the 1st and 99th percentiles. As the lagged values of NSFR and DTL are used as explanatory variables, we only keep CBs which have at least four continuous annual observations. Our final samples have 45,198 bank-year observations of 3,765 unique banks for Bankscope dataset and 92,961 observations of 8,357 unique banks for CALL report dataset.

Table 2: Definition of variables

Panel A: Variables in the frontier function	
PBT	Profit before tax
P_1	Price of loans, computed as the ratio of net interest income to net loans.
P_2	Price of other earning assets, calculated as the ratio of non-interest income to other earning assets.
W_1	Cost of funds, calculated as the ratio of interest expenses to total deposits.
W_2	Cost of labour, computed as the ratio of personnel expenses to total assets
W_3	Cost of physical assets, calculated as the ratio of overhead expenses net of personnel expenses to fixed assets
EQ	Equity capital ratio
Dummysize	A dummy variable, which is equal to 1 if a bank's total assets exceed 50 percentile of the sample's total assets in the same year and equal to 0 otherwise

Pane B: Variables in the inefficiency term-base model	
NSFR[*]	The ratio of the available stable funding (ASF) over the required stable funding (RSF). The computation of ASF and RSF relies on the weights shown in Table 1
DTL	The ratio of core deposits to loans
ADIV[*]	Asset diversification. The computation of this variable is shown in Eq. (5)
FDIV[*]	Asset diversification. The computation of this variable is shown in Eq. (6)
SIZE	The logarithm of total assets
NPL	Period non-performing loans over total loans
Crisis	A dummy variable: Financial crisis years are the years 2007 and 2008

[*]: *authors'* calculation using data from Bankscope and Federal Financial Institutions Examination Council call reports

Table 3 presents the descriptive statistics for the variables employed in this paper. The average NSFR ratio is 0.97 with a large degree of dispersion across banks, ranging from 0.71 to 2.16 for Bankscope data set. About 75 percentage of bank-years observations has NSFR ratio less than one in this data set. Among other variables, on average, a bank has DTL of 1.32, asset diversification of 0.73, fund diversification of 0.25, log asset value of 5.69, and NPL of 1.97 percent. For the call reports, however, the average NSFR ratio is 1.53 with a wide variation across banks, ranging from 0.56 to 7.14. On average, a bank has DTL of 1.17, asset diversification of 0.34, fund diversification of 0.18, log asset value of 11.87, and NPL of 1.23 percent.

Table 3: Descriptive statistics

	N	Min	P25	Mean	P50	P75	Max	STD
PANEL A: BANKSCOPE								
Variables in the frontier								
$\ln(PBT/W_3)$	45198	-6.30	-0.24	0.03	0.04	0.36	4.06	0.66
$\ln(P_1/W_3)$	45198	-1.51	-0.09	0.00	0.00	0.10	1.11	0.18
$\ln(P_2/W_3)$	45198	-0.74	-0.09	0.01	0.00	0.11	0.71	0.18
$\ln(W_1/W_3)$	45198	-2.87	-0.49	-0.10	-0.05	0.36	2.51	0.63
$\ln(W_2/W_3)$	45198	-1.44	-0.06	0.00	0.00	0.06	0.80	0.13
$\ln(EQ)$	45198	-3.56	-0.08	0.08	0.06	0.24	2.79	0.35
Dummysize	45198	0.00	0.00	0.61	1.00	1.00	1.00	0.49
Variables in the inefficiency term-base model								
NSFR	45198	0.71	0.87	0.97	0.94	1.04	1.99	0.14
DTL	45198	0.77	1.08	1.32	1.23	1.45	3.30	0.35
ADIV	45198	0.03	0.73	0.73	0.77	0.79	0.82	0.11
FDIC	45198	0.05	0.19	0.25	0.23	0.29	0.52	0.08
Size	45198	2.89	4.75	5.69	5.46	6.41	10.60	1.30
NPL (%)	45198	0.01	0.40	1.97	0.94	2.30	14.60	2.72
Crisis	45198	0.00	0.00	0.15	0.00	0.00	1.00	0.35

PANEL B: CALL REPORTS								
Variables in the frontier								
$\ln(PBT/W_3)$	92961	-11.94	-0.18	0.00	0.00	0.18	6.13	0.51
$\ln(P_1/W_3)$	92961	-6.98	-0.18	0.00	-0.01	0.17	5.24	0.40
$\ln(P_2/W_3)$	92961	-1.32	-0.19	0.00	-0.01	0.18	1.48	0.35
$\ln(W_1/W_3)$	92961	-9.45	-0.52	-0.05	0.03	0.48	6.29	0.80
$\ln(W_2/W_3)$	92961	-2.57	-2.23	-0.01	-0.01	0.19	2.75	0.38
$\ln(EQ)$	92961	-4.57	-0.10	0.03	0.02	0.16	2.99	0.32
Dummysize	92961	0.00	0.00	0.50	1.00	1.00	1.00	0.50
Variables in the inefficiency term-base model								
NSFR	92961	0.56	1.17	1.53	1.36	1.68	7.14	0.62
DTL	92961	0.48	0.90	1.17	1.07	1.33	3.49	0.42
ADIV	92961	0.00	0.25	0.34	0.38	0.46	0.55	0.18
FDIC	92961	0.00	0.01	0.08	0.05	0.16	0.53	0.20
Size	92961	9.16	11.05	11.87	11.74	12.53	16.60	1.23
NPL (%)	92961	0.01	0.02	1.23	0.03	1.50	19.37	2.27
Crisis	92961	0.00	0.00	0.15	0.00	0.00	1.00	0.35

Source: Bankscope, Federal Financial Institutions Examination Council call reports and authors' calculation.

5. Empirical results

5.1. Profit efficiency score

Table 4 summarizes the mean and standard deviation of profit efficiency scores, which show mean scores being higher for CALL report dataset than for Bankscope. Using Bankscope dataset, the mean efficiency score for the entire period is 0.76, implying that on average a bank could increase its profit by 24 percent. Another feature is that the profit efficiency has a cyclical pattern over time, increasing from 0.79 to 0.83 during the period 2001-2005 before decreasing from 0.82 to 0.61 over the period 2006-2009, and then increasing from 0.70 to 0.80 during 2010-2015. The score variability is higher during the global financial crisis (GFC) period. This cyclical trend is also observed in previous empirical studies (Gaganis and Pasiouras, 2013; Luo et al., 2016).

Table 4: Efficiency scores.

	Bankscope		Call Reports	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
2000	0.767	0.123	0.927	0.035
2001	0.769	0.117	0.930	0.031
2002	0.789	0.105	0.933	0.018
2003	0.790	0.108	0.934	0.017

2004	0.801	0.103	0.935	0.021
2005	0.818	0.100	0.934	0.026
2006	0.813	0.110	0.931	0.350
2007	0.784	0.149	0.929	0.032
2008	0.687	0.218	0.920	0.076
2009	0.663	0.227	0.911	0.114
2010	0.707	0.203	0.929	0.033
2011	0.727	0.181	0.933	0.020
2012	0.763	0.160	0.933	0.023
2013	0.781	0.140	0.933	0.018
2014	0.793	0.132		
2015	0.804	0.118		

5.2. Baseline analysis

The main focus of the present paper is to examine the relationship between liquidity in term of NSFR on profit efficiency. In the baseline analysis, we employ the NSFR to proxy for liquidity. Results in Table 5 display estimates of two specifications: one with lagged NSFR ($NSFR_{t-1}$) and another with both the lagged NSFR and its squared value ($NSFR_{t-1}^2$). The overall finding is that there is a negative impact of NSFR on bank profit inefficiency. In addition, there exists a U-shaped impact of liquidity on the bank efficiency and that the impact is consistent across two data sets from Bankscope and call reports.

Table 5: Impact of the NSFR on bank profit inefficiency scores.

	(1)		**(2)**		**(3)**		**(4)**	
	Dependent variable: $PROFIT\ INEFFICIENCY_t$							
	PANEL A: Bankscope				**PANEL B: Call Reports**			
$NSFR_{t-1}$	-4.584	***	-34.588	***	-2.454	***	-23.281	***
	(1.074)		(4.927)		(0.161)		(2.827)	
$NSFR_{t-1}^2$			14.211	***			8.961	***
			(2.078)				(0.360)	
$ADIV_{t-1}$	10.878	***	12.100	***	-20.929	***	-17.129	***
	(2.719)		(2.608)		(0.743)		(3.145)	
$FDIV_{t-1}$	6.639	***	6.293	***	-12.461	***	-49.222	***
	(1.323)		(1.235)		(0.231)		(1.100)	
$Size_{t-1}$	3.231	***	2.967	***	8.802	***	43.911	***
	(0.340)		(0.302)		(0.143)		(0.949)	
NPL_{t-1}	1.016	***	0.950	***	85.448	***	266.671	***

	(0.108)		(0.098)		(2.328)		(8.703)	
Crisis	5.626	***	5.156	***	0.791	***	6.030	***
	(0.637)		(0.570)		(0.330)		(1.665)	
Constant	-42.074	***	-24.606	***	-135.493	***	-652.373	***
	(5.246)		(4.178)		(2.237)		(14.749)	
Banks	3765		3765		8357		8357	
Yearly obs.	30069		30069		88401		88401	

This table presents the impacts of NSFR and other bank control variables on profit inefficiency. Regressions 1 and 2 use data from Bankscope and regressions 3 and 4 from Call Reports (or Federal Financial Institutions Examination Council call reports). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Results from regression 1 and 3 in Table 5 clearly show that the lagged NSFR is statistically negatively related to profit inefficiency, suggesting a positive relationship between NSFR and profit efficiency (or negative relationship between NSFR and inefficiency). The negative impact can occur because banks with more liquidity are resistant to the liquidity shortage and outperform those with less liquidity. On the asset side, we may assume that banks with higher NSFR are more revenue-effective in allocating credits and investments because they have more available capital to grant credits to big clients and invest in more profitable projects. On the funding side, we could suppose that banks with higher NSFR are more cost-effective in mobilizing external fundings in a short time. Therefore, we may conclude that banks with a higher NSFR are more efficient in their financial intermediation process because they are more optimal in both capital mobilization and allocation compared to banks with a lower NSFR. Our result is in line with the empirical research of Tsionas et al. (2015) which defines bank liquidity as total cash to total deposits and obtains a negative influence of the liquidity on the cost efficiency of European banks. However, our result considerably differs from the study of Dietrich et al. (2014) which provides evidence of no effect of NSFR on accounting profitability (including return on assets, return on equity and net interest margin).

Regressions 2 and 4 consist of the one-period lagged NSFR and its squared value to see if there exists a nonlinear influence on bank profit inefficiency. Our results confirm that the squared value of the one-period lagged NSFR has a statistically significant impact on profit inefficient. In other words, too much liquidity may have a side effect on bank performance. Our results suggest that there could be a threshold effect where a too large increase in NSFR can result in higher profit inefficiency as captured by a positive quadratic term of NSFR in regressions 2 and 4. From this perspective, an interesting question for bank managers is that what the optimal NSFR should be? Using the results in table 5, we calculated the turning point occurs when NSFR is 2.43[2] for Bankscope data set and 2.60[3] for CALL report data set. Previous studies also suggest an optimal quantity of liquid asset holdings for a bank which equates the marginal opportunity cost of liquid asset holdings to their marginal return (De Haan and van den End, 2013). Diamond (1991) proposes an optimal financial mechanism showing that maturity of both financial assets and real investments increases when market participation increases.

The statistical significance of the one-period lagged NSFR and its quadratic term suggests that the relationship between liquidity and inefficiency should be nonlinear. This finding is substantially different from previous studies which focus only on the linear effect of liquidity on bank performance. For example, Berger and Bouwman (2009) find a linearly positive effect of liquidity creation on profitability (in terms of the net surplus between the banks, borrowers and depositors). Or liquidity creation imposed a linearly negative effect on bank performance (Goddard et al., 2013; Molyneux and Thornton, 1992). More recently, Tsionas et al. (2015) examined a linear effect of liquidity[4] on technical and allocative inefficiency and found a linearly negative association.

[2] We get the result by using: $\frac{\delta Inefficiency}{\delta NSFR} = -34.588 + 14.211 \times NSFR = 0$. From this equation, we find NSFR is 2.43.

[3] We get the result by using: $\frac{\delta Inefficiency}{\delta NSFR} = -23.281 + 8.961 \times NSFR = 0$. From this equation, we find NSFR is 2.60

[4] The authors defined liquidity as a ratio of total cash to total deposits.

There are two possible explanations for the U-shaped impact of NSFR on bank profit inefficiency. On the one hand, two much stable funding incurs higher costs. A crucial factor to meet the NSFR target for banks is to enlarge their base of stable funding, mainly from long-term liabilities and core deposits. However, these funding sources are more expensive than short-term ones. On the other hand, too much liquid assets yield lower income. To have more liquid assets, banks can review their asset portfolios as well as business lines toward investing in more short-term maturity asset portfolios and substituting risk-weighted assets (RWA)-free fee income for RWA-interest income. To sum up, higher financial cost and lower income would lead to a greater inefficiency for banks with too much liquidity.

Among bank characterisktics, asset diversification and funding one are statistically significant but their coefficient signs are not consistent, positive for Bankscope data set while negative for the Call Report one. By contrast, size, non-performing loan ratio and the dummy for crisis year are both statistically significant and their coefficient signs are stable across the two data sets. The positive influence of size, non-performing loan ratio and the dummy for crisis year presents several important implications. First, the coefficient of size is positive, which implies that, on average, larger banks are more inefficient. This result is different from several previous studies (Luo et al., 2016; Tsionas et al., 2015) who find that larger banks gain more profit efficiency. We argue that the positive association between bank size and profit inefficiency can be due to limited credit growth to enhance large banks' liquidity position. Banks size has been considered as an important determinant of lending decision. Changes in credit-supply that response to liquidity requirement prevent large banks from earning more net interest margin and profitability. Previous studies also find a negative relationship between bank size and credit growth (Berger and Udell, 2006; Gavalas, 2015). In addition, large banks tend to suffer from higher loan loss provisions during the crisis and lower net interest margins than small banks (Dietrich and Wanzenried, 2011). Second, higher NPL ratio can lead to higher profit inefficiency because banks with a higher NPL ratio have to increase provisions for bad loans. This finding is in line with the one in (Gaganis and Pasiouras, 2013; Luo et al., 2016). In the same vein, Mamatzakis (2015) suggests that the positive effect becomes stronger for banks with higher inefficiency scores. Finally, crisis years of 2007 and 2008 contribute to higher profit inefficiency.

5.3. Robustness analysis

In the baseline analysis, we have used NSFR as a liquidity proxy and found a U-shaped relationship between liquidity and profit inefficiency. In this section, we follow DeYoung and Jang (2016) in employing the ratio of core deposits to loans as another liquidity indicator. We choose the ratio because the core deposits can act as a long-term source of funding for banks. Thus, the ratio is a measure for the liquidity of bank balance sheets in the sense that banks with a higher ratio are considered to have lower liquidity risk. In addition, the ratio is similar to the computation of NSFR (DeYoung and Jang, 2016).

Table 6: Impact of core deposits-to-loans ratio on bank profit inefficiency scores.

	(1)		**(2)**		**(3)**		**(4)**	
	Dependent variable: $PROFIT\ INEFFICIENT_t$							
	PANEL A: Bankscope				**PANEL B: Call Reports**			
$Deposits/Loans_{t-1}$	-1.859	***	-12.255	***	-32.228	***	-2.713	***
	(0.484)		(1.973)		(0.873)		(0.100)	
$(Deposits/Loans)^2_{t-1}$			3.370	***			0.827	***
			(0.566)				(0.027)	
$ADIV_{t-1}$	9.824	***	13.771	***	-14.726	***	-0.356	***
	(2.836)		(2.988)		(0.958)		(0.019)	
$FDIV_{t-1}$	4.487	***	2.862	**	-11.347	***	0.072	***
	(1.312)		(1.257)		(0.340)		(0.009)	
$Size_{t-1}$	3.315	***	3.136	***	16.179	***	0.004	*

	(0.351)		(0.323)		(0.214)		(0.002)	
NPL_{t-1}	1.012	***	0.975	***	120.714	***	-0.167	
	(0.109)		(0.102)		(2.972)		(0.107)	
Crisis	5.769	***	5.424	***	0.295		0.082	***
	(0.658)		(0.607)		(0.391)		(0.007)	
Constant	-43.455	***	-36.819	***	-232.501	***	23.687	***
	(5.386)		(4.696)		(3.324)		(1.113)	
Banks	3765		3765		8317		8317	
Yearly observations.	30069		30069		86707		86707	

This table presents the impacts of core deposits-to-loans ratio and other bank control variables on profit inefficiency. Regressions 1 and 2 use data from Bankscope and regressions 3 and 4 from Call Reports (or Federal Financial Institutions Examination Council call reports). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Table 6 presents the estimation results of our robustness analysis. With regard to the linear impact of the ratio of core deposits to loans, the ratio has a statistically significant and negative impact on bank profit inefficiency in for both data sets (as shown in regressions 1 and 3). This effect implies that liquidity enhances profit efficiency, lending support to the argument of the public interest theory (Barth et al., 2006). The theory argues that stricter regulations help to align the benefits of bank owners, depositors and other creditors, resulting in more careful lending and better performance. To some extent of liquidity, the revenue of lending exceeds the cost of funding, leading to higher net interest margin and thus profit before tax. Regarding the nonlinear impact of the ratio of core deposits to loans, the quadratic term of the ratio as shown in regressions 2 and 4 obtains positive and statistically significant coefficients. This result supports a nonlinear effect of the ratio on bank profit inefficiency.

Among variables of bank characteristics, coefficients of asset and funding diversification, non-performing loan ratio and the dummy crisis year dummy variables are either inconsistent or not statistically significant across four regressions in Table 6. Only coefficients of size are consistently positive and statistically significant, suggesting that banks with larger size may promote profit inefficiency.

In this robustness analysis, we confirm that the influence of liquidity (proxied by the core deposit to loans ratio) on profit inefficiency is similar to that in the baseline analysis. The sign of the linear impact is negative for both baseline and robustness analyses and for both data sets, implying that banks with a higher liquidity ratio can have a lower profit inefficiency score. However, the sign of the quadratic term of the two liquidity indicators (NSFR and the core deposit to loans ratio) are positive for both analyses, indicating that banks with too much liquidity can lead to a higher profit inefficiency score. For bank characteristics, only size obtains a consistent sign of coefficients. Thus size together with liquidity are the most stable driving factors to explain profit inefficiency.

6. Conclusion

This paper examines empirically the relationship between liquidity on bank profit efficiency for commercial banks in the U.S over the period 2001-2015 using data from two sources: Bankscope and Federal Financial Institutions Examination Council Call reports. Efficiency scores estimated using Bankscope dataset are lower than those using Call reports. More importantly, we delve more deeply into the non-linear relationship between bank efficiency and the NSFR under the Basel III framework which was designed to promote the stability of individual banks and the whole system. Our empirical results show that a non-linear relationship exists between NSFR and bank efficiency. More specifically, the results suggest that modest intensification in liquidity helps to improve bank profit efficiency. However, too much liquidity enlargement could ruin the profit efficiency. These results are robust in both datasets.

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